CONTINUOUS-TIME SYSTEMS IDENTIFICATION BASED ON ITERATIVE LEARNING CONTROL

Fumitoshi Sakai * **Toshiharu Sugie** **

* *Department of Mechanical Engineering*
Nara National College of Technology
Yamatokoriyama, Nara 639-1080. Japan
** *Department of Systems Science*
Graduate School of Informatics, Kyoto University
Uji, Kyoto 611-0011. Japan

sakai@mech.nara-k.ac.jp
sugie@i.kyoto-u.ac.jp

Abstract: The paper proposes a novel approach to identification of continuous-time systems from sampled I/O data. The coefficients of plant transfer functions are directly identified by applying an iterative learning control which enables us to achieve perfect tracking for uncertain plants by iteration of trials. Furthermore, one way to make the method robust against the measurement noises is shown. One of the merits of the proposed method is that it does not require time-derivative of I/O signals. In addition, it indicates us the estimation accuracy explicitly through tracking control experiments. Numerical examples are given to illustrate the effectiveness of the proposed method.

Keywords: Continuous-time, System identification, Iterative learning control

1. INTRODUCTION

The identification of continuous-time systems is important in a wide variety of problems. There are two ways to obtain a continuous-time model. An indirect way, suggested by the discrete-time model identification methodology, is to estimate a discrete-time model first and then convert it into a continuous-time model. A direct approach, suggested by the continuous-time model identification methodology, consists in identifying directly a continuous-time model from the sampled data. The basic difficulty of the direct approach is in handling of the non-measurable time-derivatives. Many methods to circumvent the need to reconstruct these time-derivatives have been devised. A comprehensive survey of these techniques has been first given by (Young, 1981) and then by (Unbehauen and Rao, 1990). A book has also been devoted to these so-called direct methods (Sinha and Rao, 1991). The Continuous-Time System Identification (CONTSID) toolbox has been developed on the basis of these methods (Garnier and Mensler, 1999; Garnier and Mensler, 2000; Garnier *et al.*, 2003).

On the other hand, in the iterative learning control for obtaining the input, which yields predetermined output by the iteration of trial, such a method as to employ time-derivative of errors is proposed(Arimoto *et al.*, 1984; Sugie and Ono, 1991). Those are not suitable under the condition when time-derivative of a high order has to be utilized, and Hamamoto et al. propose an iterative learning control within prescribed input-output subspace, showing that even when precise information of the model is not available, time-derivative of tracking error is not required to achieve perfect tracking(Hamamoto and Sugie, 2001). Further, Sugie et al. pointed out the possibility of the identification of the continuous-time system through the iterative learning control within the prescribed input-output subspace(Sugie and Hamamoto, 2002).

In this paper, while paying attention to the iterative learning algorithm within prescribed input-output subspace, the continuous-time identification method is proposed from an entirely different viewpoint from the conventional one. Firstly, by using the iterative learning algorithm, it is shown that from the sampled I/O data, parameters of the continuous-time system can be identified without the use of time-derivative, and from numerical examples, its validity is illustrated. Then, a learning update law is proposed, which becomes robust against measurement noise. Furthermore, since parameters are identified while performing a follow-up control to the target trajectory, it is demonstrated that the proposed method possesses advantages, which conventional identification method does not have, such as users can confirm the identification accuracy by watching the tracking error quantity.

In this paper, the superscript of the variables denotes the trial number of the experiment and the subscript of those denotes the element number of a set or a matrix. Namely the input u of the kth trial is denoted by u^k and the ith element of the vector x is denoted by x_i. And u^0 is the initial input in the learning iteration.

2. THE IDENTIFICATION ALGORITHM

2.1 Iterative learning algorithm within prescribed I/O subspace

We consider a continuous-time SISO system whose input $u(t)$ and output $y(t)$ are related by a linear constant coefficient differential equation of order n_f

$$\sum_{i=0}^{n_f} \alpha_i \frac{\mathrm{d}^i y(t)}{\mathrm{d}t^i} = u(t). \tag{1}$$

In this system, when using the time-varying matrix

$$\begin{aligned} V_d(t) &\triangleq \left[v_{d0}(t), v_{d1}(t), \dots, v_{dn_f}(t)\right] \\ &= \left[r(t), \frac{\mathrm{d}r(t)}{\mathrm{d}t}, \dots, \frac{\mathrm{d}^{n_f} r(t)}{\mathrm{d}t^{n_f}}\right] \end{aligned} \tag{2}$$

determined by a given target trajectory $r(t) \in L_2[0,\ T]$ and its time-derivative function, the optimal input $u^*(t)$ for generating the target trajectory (that is, for obtaining $y(t) = r(t)$) is uniquely determined as

$$u^*(t) = V_d(t)\boldsymbol{\alpha} \tag{3}$$

where

$$\boldsymbol{\alpha} \triangleq [\alpha_0, \alpha_1, \dots, \alpha_{n_f}]^T.$$

In (Hamamoto and Sugie, 2001), the input $u(t)$ in the iteration and the update law of the coefficient $\boldsymbol{\alpha}$ is given as

$$u^{k+1}(t) = V_d(t)\boldsymbol{\alpha}^{k+1} \tag{4}$$

$$\boldsymbol{\alpha}^{k+1} = \boldsymbol{\alpha}^k + H \int_0^T V_d(t)^T V_d(t) dt \tag{5}$$

where the error signal between the target trajectory $r(t)$ and the output $y^k(t)$ is determined as $e^k(t) = r(t) - y^k(t)$ in each trial. Further, $H \in \boldsymbol{R}^{(n_f+1)\times(n_f+1)}$ is the learning gain. When the learning gain which satisfies iterative stability is chosen,

$$e^k(t) \to 0, \quad (k \to \infty)$$

is achieved. Then, the input $u(t)$ and output $y(t)$ correspond one-to-one,

$$u^k(t) \to u^*(t)$$

so that when $\int_0^T V_d(t)^T V_d(t) dt > 0$, the coefficient is uniquely determined by (3), therefore,

$$\boldsymbol{\alpha}^k \ \to \ \boldsymbol{\alpha}$$

is obtained.

2.2 Continuous-time systems identification from sampled I/O data

Based on the fundamental idea of the continuous-time system identification mentioned in Section 2.1, an algorithm utilizing the sampled I/O signals is concretely derived.

The input signal $\{u^k(nT_s),\ \ y^k(nT_s);\ \ n = 0, 1, \dots, N\}$ of the k-th trial, which was sampled with the sampling period T_s, is converted into vectors $\boldsymbol{u}^k \in \boldsymbol{R}^{N+1}$ and $\boldsymbol{y}^k \in \boldsymbol{R}^{N+1}$.

In the same way, the optimal input, target trajectory and tracking error are also converted into vectors $\boldsymbol{u}^* \in \boldsymbol{R}^{N+1}$, $\boldsymbol{r} \in \boldsymbol{R}^{N+1}$ and $\boldsymbol{e}^k \in \boldsymbol{R}^{N+1}$ respectively. Additionally, the time-varying matrix $V_d(t)$ is sampled with the sampling period T_s, and the longitudinally set matrix is defined as follows;

$$\tilde{V}_d \triangleq \begin{bmatrix} v_{d0}(0) & v_{d1}(0) & \dots & v_{dn_f}(0) \\ v_{d0}(T_s) & v_{d1}(T_s) & \dots & v_{dn_f}(T_s) \\ \vdots & \vdots & \dots & \vdots \\ v_{d0}(NT_s) & v_{d1}(NT_s) & \dots & v_{dn_f}(NT_s) \end{bmatrix} \tag{6}$$

where, it is assumed that the matrix $\tilde{V}_d \in \boldsymbol{R}^{(N+1)\times(n_f+1)}$ satisfies $\mathrm{rank}\tilde{V}_d = n_f + 1$. Further, in order to facilitate the description of the algorithm, for convenience, $\tilde{V}_d$ is expressed by the product of a matrix, which has orthogonal columns $U \triangleq \left[\boldsymbol{f}_0, \boldsymbol{f}_1, \ldots, \boldsymbol{f}_{n_f}\right] \in \boldsymbol{R}^{(N+1)\times(n_f+1)}$ and an upper triangular matrix $R \in \boldsymbol{R}^{(n_f+1)\times(n_f+1)}$ by QR decomposition

$$\tilde{V}_d = UR, \qquad U^T U = I_{n_f+1}. \tag{7}$$

Then, the problem of this paper is to identify the coefficient $\{\alpha_i;\ i = 0, 1, \ldots, n_f\}$ of (1) from I/O signals $\boldsymbol{u}^k$ and $\boldsymbol{y}^k$ of the system by the iterative learning. Now, by (4), the input $\boldsymbol{u}^k$ of the k-th trial is defined by using an appropriate coefficient vector $\boldsymbol{a}^k \in \boldsymbol{R}^{n_f+1}$ as

$$\boldsymbol{u}^k = U\boldsymbol{a}^k. \tag{8}$$

From (4), we have $\boldsymbol{a}^k = R\boldsymbol{\alpha}^k$. The corresponding output can be expressed by using appropriate vectors $\boldsymbol{b} \in \boldsymbol{R}^{n_f+1}$ and $\boldsymbol{c} \in \boldsymbol{R}^{N-n_f}$ as

$$\boldsymbol{y}^k = U\boldsymbol{b}^k + U^{\perp}\boldsymbol{c}^k \tag{9}$$

where, $U^{\perp} \in \boldsymbol{R}^{(N+1)\times(N-n_f)}$ expresses a matrix, which aligns the base of $\ker U^T$.

Further, these coefficient vectors corresponding to the optimal input $\boldsymbol{u}^*$ and the target trajectory $\boldsymbol{r}$ are defined as $\boldsymbol{a}^*$ and $\boldsymbol{b}^*$ respectively, and the coefficient error as

$$\boldsymbol{\varepsilon}_u^k \triangleq \boldsymbol{a}^* - \boldsymbol{a}^k, \qquad \boldsymbol{\varepsilon}^k \triangleq \boldsymbol{b}^* - \boldsymbol{b}^k \tag{10}$$

Then, an update law corresponding to (5) is given by

$$\begin{aligned} \boldsymbol{a}^{k+1} &= \boldsymbol{a}^k + HU^T\boldsymbol{e}^k \\ &= \boldsymbol{a}^k + H\boldsymbol{\varepsilon}^k. \end{aligned} \tag{11}$$

The convergence condition of the learning update law will be shown.

Between the coefficient vectors $\boldsymbol{a}^k$ and $\boldsymbol{b}^k$, there is a certain matrix $L_f \in \boldsymbol{R}^{(n_f+1)\times(n_f+1)}$, which is uniquely determined by (1), and the following equation is realized.

$$\boldsymbol{b}^k = L_f\boldsymbol{a}^k \tag{12}$$

The matrix L_f can be obtained by the output, when $n_f + 1$ of base vectors $\{\boldsymbol{f}_i;\ i = 0, 1, \ldots, n_f\}$ are input into the system as a pilot study prior to the iterative learning. The i-th base $\boldsymbol{f}_i$ is added as an input, the corresponding output be $\boldsymbol{\phi}_i$, and from the following equation $\boldsymbol{\xi_i} = [\xi_{i0}, \cdots, \xi_{in_f}]^T \in \boldsymbol{R}^{n_f+1}$ be obtained.

$$\boldsymbol{\xi_i} \triangleq \operatorname{argmin} \left\| \boldsymbol{\phi}_i - \sum_{j=0}^{n_f} \boldsymbol{\xi}_{ij}\boldsymbol{f}_j \right\| \tag{13}$$

Obtained $\boldsymbol{\xi_i}$ is the i-th column of L_f, and L_f can be obtained by using each base. From (12), (11) of the learning law becomes as follows;

$$\boldsymbol{a}^{k+1} = \boldsymbol{a}^k + HL_f(\boldsymbol{a}^* - \boldsymbol{a}^k).$$

Thereby,

$$\boldsymbol{\varepsilon}_u^{k+1} = (I - HL_f)\boldsymbol{\varepsilon}_u^k$$

is obtained, and the condition for the learning to converge is given by

$$\rho(I - HL_f) < 1 \tag{14}$$

where, $\rho(A)$ denotes the spectral radius of matrix A.

When the learning process converges, $\boldsymbol{a}^k \rightarrow \boldsymbol{a}^*$ is realized and the true value $\boldsymbol{\alpha}$ of the parameter is identified by

$$\boldsymbol{\alpha} = R^{-1}\boldsymbol{a}^*.$$

As a candidate for the learning gain, which satisfies the condition of (14), $H = L_f^{-1}$ will be used here. Actually, estimated value $\hat{L}_f$ of L_f can be obtained from (13), therefore, $H = \hat{L}_f^{-1}$ is utilized as the learning gain.

2.3 Learning update law utilized past information

As mentioned above, since inner product of error is taken in the update law of (11), the measurement noise contained in $\boldsymbol{\varepsilon}^k$ is averaged to have smaller affect. However, since the information of the previous trial only is used, therefore, small perturbation occur in $\boldsymbol{\varepsilon}^k$ for every iteration, so that as a result, although available I/O data increase with the increase of the trial iteration, it cannot be reflected to the improvement of the identification accuracy. Then, by effectively utilizing the information in the trial of the past and upon averaging the perturbation in the iteration direction, it is considered to be expanded into a learning update law, which satisfies learning convergence conditions.

Firstly, for $\boldsymbol{\varepsilon}^k$ as a filter $F(z)$ for reducing the perturbation caused in each trial, a first-order low-pass filter

$$F(z) = \frac{(1-\lambda)z}{z-\lambda} \tag{15}$$

is considered to be used. Where, z denotes z-transform operator and the coefficient λ be the constant of $\lambda \in [0,\ 1]$. $\boldsymbol{\varepsilon}^k$ can be considered as a discrete-time signal in the iteration direction, and its z-transform can be expressed as $\mathcal{Z}\{\boldsymbol{\varepsilon}^k\}$. When the input signal to the filter $F(z)$ of (15) is $\boldsymbol{\varepsilon}^k$ and the output signal $\hat{\boldsymbol{\varepsilon}}^k$,

$$\mathcal{Z}\{\hat{\boldsymbol{\varepsilon}}^k\} = \frac{(1-\lambda)z}{z-\lambda}\mathcal{Z}\{\boldsymbol{\varepsilon}^k\} \tag{16}$$

is shown, and when being expressed by the difference equation, it will be

$$\hat{\varepsilon}^k = \lambda \hat{\varepsilon}^{k-1} + (1-\lambda)\varepsilon^k. \quad (17)$$

The output signal $\hat{\varepsilon}^k$ of the filter is utilized as the learning update law. The filter coefficient λ can be considered as a forgetting factor, and when it is set as $1 - \lambda \ll 1$, it will be to calculate the ensemble mean of ε^k sequentially until the k-th trial, by multiplying a larger weight λ with the filter output signal $\hat{\varepsilon}$ of the previous trial, and a smaller weight $1-\lambda$ with ε^k of the k-th trial, resulting in the reduction of the perturbation in the iteration direction.

A filter $F(z)$ will be applied to the update law of (11). From the viewpoint of the stability of the iteration, for the coefficient $\boldsymbol{a}^k$, the following equation using the similar filter is considered.

$$\mathcal{Z}\{\boldsymbol{a}^{k+1}\} = F(z)\mathcal{Z}\{(\boldsymbol{a}^k + H\boldsymbol{\varepsilon}^k)\} \quad (18)$$

Using the filter of (15), (18) is expressed by the difference equation,

$$\begin{aligned}\boldsymbol{a}^{k+1} &= \hat{\boldsymbol{a}}^k + H\hat{\boldsymbol{\varepsilon}}^k \\ &= \lambda(\hat{\boldsymbol{a}}^{k-1} + H\hat{\boldsymbol{\varepsilon}}^{k-1}) + (1-\lambda)(\boldsymbol{a}^k + H\boldsymbol{\varepsilon}^k).\end{aligned} \quad (19)$$

Here, $\hat{\boldsymbol{a}}$ is the output signal of the filter, which has a similar meaning with $\hat{\varepsilon}$ in (17), being specified as $\hat{\boldsymbol{a}}^0 = 0$ and $\hat{\varepsilon}^0 = 0$. In the update law, when the filter coefficient is $\lambda = 0$, which results in (11), and the update law of (19) becomes an extended update law, which includes the update law of (11) as its special case. Next, the convergence condition of the update law will be shown like Section 2.2. When the (19) is organized using the relation $\boldsymbol{\varepsilon}^k = L_f \boldsymbol{\varepsilon}_u^k$, the following relation can be obtained,

$$\boldsymbol{\varepsilon}_u^{k+1} = (I - HL_f)\left\{\lambda\hat{\boldsymbol{\varepsilon}}_u^{k-1} + (1-\lambda)\boldsymbol{\varepsilon}_u^k\right\}. \quad (20)$$

When $\boldsymbol{x}^k \triangleq \left[\boldsymbol{\varepsilon}_u^k,\ \hat{\boldsymbol{\varepsilon}}_u^{k-1}\right]^T$ is defined as a new state vector,

$$\boldsymbol{x}^{k+1} = A\boldsymbol{x}^k \quad (21)$$

will be obtained. Where,

$$A \triangleq \begin{bmatrix}(1-\lambda)(I-HL_f) & \lambda(I-HL_f) \\ (1-\lambda)I & \lambda I\end{bmatrix}.$$

Thus,

$$\rho(A) < 1 \quad (22)$$

will become a necessary and sufficient condition for satisfying the iteration stability in the update law of (19), so that when this condition is fulfilled, the coefficient of the system can be identified.

Remark 1. As mentioned before, when the measurement noise exist, the true L_f cannot be obtained, so that it cannot be confirmed whether the iteration stability is fulfilled by (22). However, by calculating the uncertainty contained in the estimated value $\hat{L}_f$ of L_f, it may be possible to design the learning gain H, which satisfies (22) within the range of its uncertainty.

3. NUMERICAL EXAMPLE

In this section, we present a simple simulation example to illustrate the properties of our proposed method. This example is based on the following third-order continuous-time system;

$$P(s) = \frac{1}{s^3 + 10s^2 + 30s + 8}$$

The time interval $[0,\ T]$ is $T = 3$[s], and the sampling period being 5[ms]. Assuming that the order of the target system is not precisely known, the system is supposed to be of the fourth order, and the target trajectory $r(t)$ is given according to the unit step response

$$P_r(s) = \frac{10^4}{(s+10)^4} \quad (23)$$

Further, a time-varying matrix $V_d(t)$, which is defined by the target trajectory $r(t)$ and its time-derivative function, is given by the following;

$$V_d(t) = \left[r(t), \frac{\mathrm{d}r(t)}{\mathrm{d}t}, \frac{\mathrm{d}^2r(t)}{\mathrm{d}t^2}, \frac{\mathrm{d}^3r(t)}{\mathrm{d}t^3}, \frac{\mathrm{d}^4r(t)}{\mathrm{d}t^4}\right]$$

and the output of the system is added with the white measurement noise shown by the following;

$$|v(t)| < 2.0 \times 10^{-3}, \ \ \forall t \in [0,\ T].$$

Assuming that the initial condition of the system is 0 and with the initial condition $u^0(t) = 0$, the result of 100 iterations is shown below. According to Section 2.2, the coefficient $\boldsymbol{\alpha}^k$ is calculated for every trial, the plotted result being shown in **Fig.1**. Though the estimated parameters vary in each trial, it is found that the denominator coefficient of the target system is almost accurately estimated. Further, the coefficient α_4 of the order is estimated as approximately 0, which does not exist in the target system, so that it is possible to perform identification even when the order of the target system is not precisely known.

In the update law of (11), since inner product of the error is taken, the affect of the measurement noise for each trial is averaged, therefore, the affect on the input $\boldsymbol{u}^{k+1}$ is small, which is used for the next trial. However, when the affect of the measurement noise is considered from the viewpoint of the direction of iteration, independent measurement noise is added in each trial. Further,

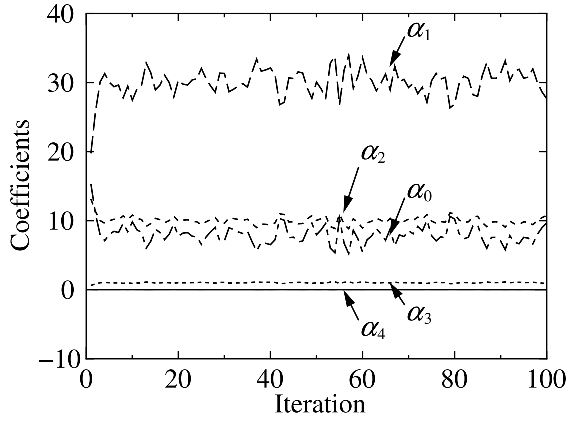

Fig. 1. Identified coefficients $\boldsymbol{\alpha}^k$ using update law of (11)

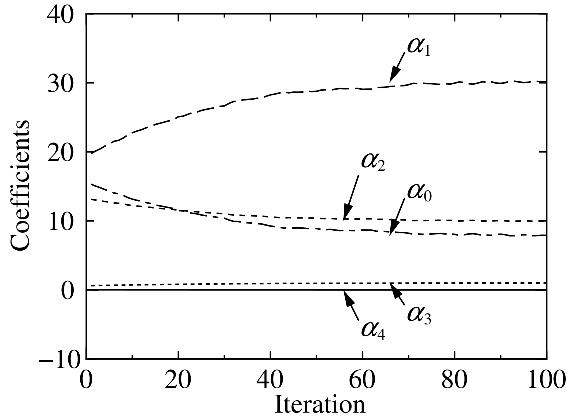

Fig. 2. Identified coefficients $\boldsymbol{\alpha}^k$ using update law of (19)

since $H\boldsymbol{\varepsilon}^k$ is calculated for each trial, when the learning gain H is ill-conditioned, a small perturbation included in $\boldsymbol{\varepsilon}^k$ may result in a large perturbation in the coefficient of the target system. The condition number of the learning gain used for the numerical example is $\mathrm{cond}(H) = 2.523 \times 10^3$, and this may cause the deterioration of the identification accuracy.

In a similar numerical example, the order of the target system is assumed to be unknown, and the result of identification using the update law of (19) in the 4-th system is shown in the following. The filter coefficient is specified as $\lambda = 0.95$. The result of the calculation and plot of the coefficient $\boldsymbol{\alpha}^k$ for each trial is shown in **Fig.2**. Although the convergence is slow because of the filter, it can be confirmed that the result is converged to each coefficient of the target system, obtaining a better result compared with **Fig.1**.

With these results, we can confirm that parameters of the continuous-time system can be identified by using the iterative learning algorithm within prescribed input-output subspace and without the use of time-derivative of I/O signals.

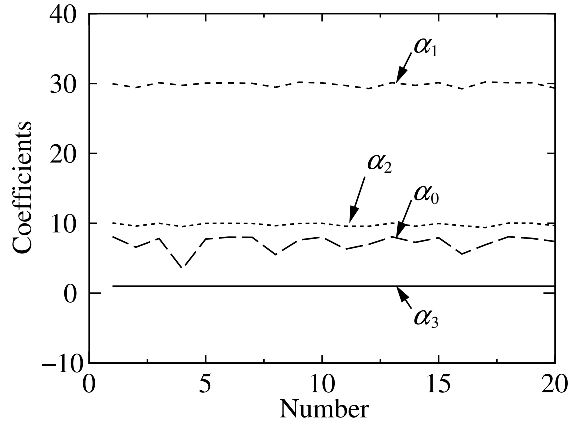

Fig. 3. Identified coefficients $\boldsymbol{\alpha}^k$ using FMF method

Next, the comparison will be made with the conventional continuous-time system identification method. Because conditions of identification, such as input signal to be used, are different, a comparison cannot simply be performed with regard to the identification accuracy, however, an example of the identification result by FMF(Fourier Modulating Function) method will be shown for reference. It is assumed here that the order of the target system is known to be three and the sampling period being 5 [ms]. If we assume that the plant is of the fourth order as before, it turned out that the identification result is quite poor. It is assumed that the input signal is white noise and as for the output signal, the signal is contaminated with white measurement noise. The magnitude of the noise was defined in such a way that the measurement noise signal ratio (NSR) to the output is approximately equal to those of the conventional numerical examples. The number of sampled I/O data is 601, which is equal to the number of sampled I/O data employed for one trial of the numerical example in a proposed method, and 20 pairs of I/O data were prepared. The plot of the coefficient $\boldsymbol{\alpha}^k$, which was identified by using each I/O data is shown in **Fig.3**. In this numerical example, it can be confirmed that with this proposed method, when compared with the conventional identification method, a favorable identification accuracy is obtained without trial and errors and with less I/O data.

4. EVALUATION OF IDENTIFICATION ACCURACY

In this section, the identification accuracy will be evaluated for numerical examples in Section 2.3 and 3.2.

Firstly, it is confirmed that, in the identification by the update law using the filter of (19), the identification accuracy is improved in each trial by Hankel norm $\|P(s) - \hat{P}(s)\|_H$ of the error system

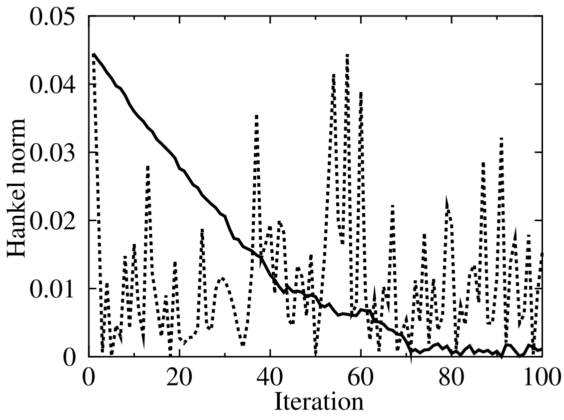

Fig. 4. Hankel norm $\|P(s) - \hat{P}(s)\|_H$

(**Fig.4**). In the figure, the solid line shows the case when $\lambda = 0.95$ is chosen in the update law of (19), and the dotted line showing $\lambda = 0$, that is, the one using the update law of (11). The filter coefficient λ defines the relation of trade-off between the attenuation rate of the perturbation included in ε^k and the speed of convergence in learning. Looking at the Hankel norm of the error system, the role and effect of the filter coefficient λ clearly appear.

The proposed method is to perform the identification of the target system based on I/O signals, while making the output follow the target trajectory, which was given in the iterative learning control, having the following advantages;

- Pre-information of the target system is little, and it is not necessary to prepare I/O signals in advance like conventional identification methods and to perform pre-processing, therefore, trial and errors in the identification operation is hardly required.
- By utilizing the iterative learning algorithm within prescribed input-output subspace, time-derivative of I/O signals is not required. On the contrary, an averaging operation by inner product is used.
- The decision whether the identification is possible or not is equivalent to the convergence of the iterative learning control process, and when the learning is achieved, the identification result can be obtained, which ensure a certain target tracking accuracy, and at the same time, the validity of the identification result being investigated.

5. CONCLUSION

In this paper, we have proposed an identification method for a class of linear continuous-time systems based on the iterative learning control (ILC) method, which is entirely different from conventional ones in a sense that no information on time-derivative of I/O signals is necessary at all. First, we showed the basic idea on the use of ILC to the identification. Then its concrete digital implementation has been given explicitly. Second, one way to make the method robust against the measurement noises has been proposed. Finally, numerical examples are given to illustrate the effectiveness of the proposed method.

At the current stage, the robustness of our method against measurement noises are similar to the existing ones and it can be applicable to a restricted class of systems. However, since the identification of parameters is done through tracking control, we are able to confirm the quality of the identified system model by watching the actual tracking error. This may be some advantage compared to the conventional ones. Therefore, it is considered to be meaningful as the first step toward a new framework of continuous-time system identification.

REFERENCES

Arimoto, S., S. Kawamura and F. Miyazaki (1984). Bettering operation of robotics. *Journal of Robotic System* **1**(2), 123–140.

Garnier, H. and M. Mensler (1999). Contsid: a continuous-time system identification toolbox for matlab. In: *Proc. of the 5th European Control Conference.*

Garnier, H. and M. Mensler (2000). The contsid toolbox: a matlab toolbox for continuous-time system identification. In: *Proc. of the 12th IFAC Symposium on System Identification.*

Garnier, H., M. Gilson and E. Husestein (2003). Developments for the matlab contsid toolbox. In: *Proc. of the 13th IFAC Symposium on System Identification.*

Hamamoto, K. and T. Sugie (2001). An iterative learning control algorithm within prescribed input-output subspace. *Automatica* **37**(11), 1803–1809.

Sinha, N.K. and G.P. Rao (1991). *Identification of Continuous-Time Systems.* Kluwer Academic Publishers. Dordrecht.

Sugie, T. and K. Hamamoto (2002). Iterative learning control - an identification oriented approach. In: *Proc. of SICE Annual Conference.*

Sugie, T. and T. Ono (1991). An iterative learning control law for dynamical systems. *Automatica* **27**(4), 729–732.

Unbehauen, H. and G.P. Rao (1990). Continuous-time approaches to system identification - a survey. *Automatica* **26**(1), 23–35.

Young, P. (1981). Parameter estimation for continuous-time models - a survey. *Automatica* **17**(1), 23–39.